Statistical-based Analysis of Thermally Induced Errors in Computer Numerical Control (CNC) Machining Center

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Abstract

Thermal error modeling using the temperature data obtained from different thermal key points is one of the most basic requirements for thermal error compensation in CNC machining centers. Effective thermal error compensation relies on the accurate prediction of the time-variant thermal error during machining. The increase in number of thermal key points not only increases prediction noise in the thermal error model but is also very cost effective. Hence, optimization of thermal key points is essential for accurate prediction of thermal behaviour of machine tool. In this study, the thermal key points of horizontal feed drives of a vertical CNC machine are optimized based on sensitivity analysis. A non-linear statistical regression thermal error prediction model is developed by using the temperature data obtained from the optimized key points. Thermal errors predicted before and after sensitivity analysis of thermal key points using statistical model are presented. The developed model can be interfaced to controller through microprocessors in order to monitor and compensate the thermal deformations. Further, the method can be extended to develop the mathematical model for vertical axis feed drive also.

Keywords

CNC Machine Tool; Sensitivity Analysis; Thermal Error Modelling Using Regression Analysis

Introduction

CNC machine tools are most commonly used in mass production shop floors of various sectors including automotive, aerospace, defence, etc. The ongoing research and development (R&D) activities in defence sector have put many challenges to shop floor engineers in terms of repeatability of the components being produced with the close tolerance. One of the reasons for the challenge is the inaccuracy of machine tools. This inaccuracy in itself is a major contributor to work piece errors. Among the various sources of machine tool errors, thermally-induced errors contribute to 40–70% followed by geometric errors. As the temperature field of a machine tool changes constantly according to the working cycle and environmental conditions, thermal problems become more complicated than geometric problems.

Apart from thermal error minimisation through design optimization in the design stage for new machine tools, thermal error compensation is the only alternative in the case of existing machine tools. Thermal error modelling using the temperature data obtained from different thermal key points is one of the basic requirements for thermal error compensation. Effective thermal error compensation relies on accurate prediction of the time-variant thermal error using temperature sensors during machining. The increase in number of thermal key points not only increases noise in the thermal error model, but is a costly affair. Hence, optimization of thermal key points is essential for accurate prediction of thermal behaviour .

Most recently, researchers have used various techniques like step-wise regression analysis, engineering judgement, artificial neural network and correlation analysis for optimization of thermal error key points. Yang et al optimized thermal key points in their investigation on CNC turning center by thermal mode analysis. However, this engineering judgment of thermal mode analysis becomes complicated when the number of machine elements increases due to increase in the number of axes. Lee et al have used grouping approach considering statistical mean square error. They used both the grouping approach for optimization of thermal error and the thermal key points in vertical and horizontal machining centres. Though this method helps in optimizing the thermal key points, it is both tedious and time consuming to

estimate the correlation between all the key points of a group. Rui et al used correlation grouping using finite element analysis for optimization of thermal key points in a machine tool. This method is best suited to predict the virtual thermal key points without conducting experiments. However, the reliability of this method depends mainly upon the knowledge of boundary conditions.

Sensitivity analysis is another technique for optimization of thermal key points which has been adopted by a few of the researchers. No one has made an attempt to optimize the thermally induced errors in CNC machine using statistical methods, engineering sense and sensitivity technique. The main advantage of the statistical approach is that the compensation algorithm is usually a part of the common machine control system. Therefore this can be dedicated to optimizing thermal key points using sensitivity analysis. Further, based upon the data obtained from optimized key points, a thermal error model for feed drive system of three axes vertical machining center using a non-linear statistical regression method has been proposed. A comparison of the thermal error predicted prior to and after performing sensitivity analysis for thermal key point selection has also been presented.

In the next section, the thermal analysis of the feed drive system is presented. While the third section presents the concept of thermal sensitivity analysis. The fourth section presents the error prediction model using non-linear regression method. In the fifth section, a comparison of thermal error predicted by the model developed using minimized thermal key points and experimentally measured readings is presented.

Thermal Error Analysis

If the machine structure is taken into consideration as a whole, there are three main thermal error factors: namely, 1) the machine structure distortion caused by coolant temperature variation, 2) the spindle temperature variation and 3) the ball screw temperature variation. Researchers have observed that, the positioning accuracy is one of the predominant factors among the main thermal error factors which depend mainly on the feed drive ball screw and nut temperature variation. There are two basic thermal error modes, namely, thermal expansion and thermal bending of machine element resulting from thermal error factors. Though there are basically two thermal modes, as the machine structure has large assemblies it is still not easy to determine the influential error modes. Also the influence of a particular thermal mode on a specific machine component is difficult to analyse.

Considering the observations noticed by Ramesh et al in their experimental investigations on three axes Vertical Machining Center, the feed drive system alone has been analysed in this study. As per the dictates of engineering sense, heat is more likely to be intense near the source of heat generation and based on this principle, the thermal sources are identified. The feed drive system consists of a ball-screw and nut, LM guideways, servo motor, and support bearings. Except in the motor, the heat source in all other elements is due to sliding friction between the mating parts. The details of placement of sensors are explained in the next section.

Experimental Investigation

Placement of Sensors

The locations of various thermal sensors (PT-100) are as follows: drive motor one in number, per feed drive unit (T8, T10), drive screw support bearings two in number, per feed drive unit (T8, T9, T10, T11), ball screw nuts (T12, T13) and four guideway supports for X (T0,T1,T2,T3) and Y (T4,T5,T6,T7) axis feed drive units as shown in Fig. 1-3

The PT-100 thermal sensors are wrapped in the metal foil and brazed at the key points. This ensures the firm contact between the sensors and machine parts. Further, a cotton wick is put on the metal foil and adhesion tape is used so as to ensure the secured

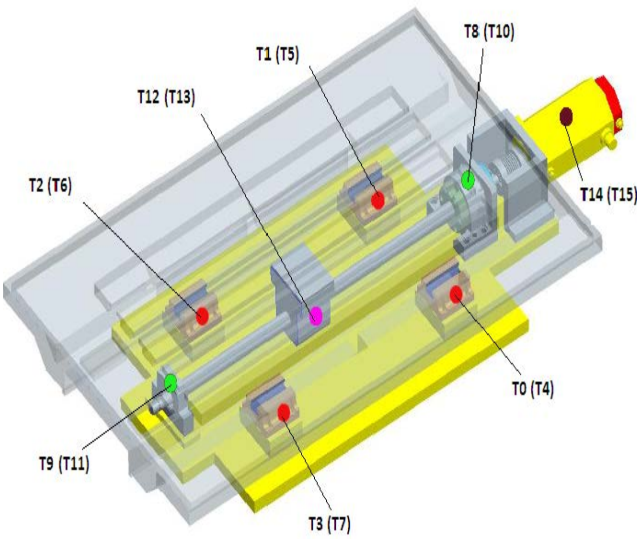

FIG.1 PLACEMENT OF TEMPERATURE SENSORS ON FEED DRIVE SYSTEM

FIG.2. EXPERIMENTAL SETUP WITH PLACEMENT OF THERMAL SENSORS ON KEY LOCATIONS

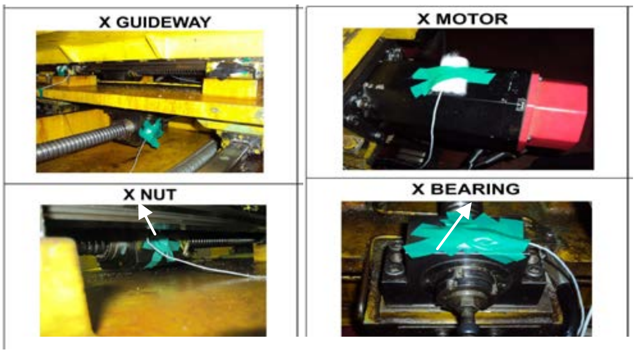

FIG.3 TEMPERATURE SENSORS PLACED ON GUIDEWAY, B) MOTOR C) BALL-SCREW NUT, D) END SUPPORT BEARING

position of the cotton wick and to protect from any liquid like oil/coolant from falling upon the sensor. The temperature key points shown within brackets correspond to Y-axis feed drive. In addition to the above temperature measurements, the ambient temperature fluctuation is also monitored by sensor number 17 (This is not shown in Fig1). The deformations at TCP (Tool Center Point) along X and Y-components are measured using two non-contact type eddy current displacement (Micro-Epsilon's eddy NCDT 3010, Measuring range: 6 mm, Linearity: ≤ ±0.25% Full Scale Output (FSO), Static repeatability: 0.6 μm, Resolution: 0.005% FSO) displacement sensors.

Measurement of Temperature and Thermal Displacement

In the LabVIEW front page, a virtual circuit was developed according to the instrumentation used in the experiment. The measurements were updated on a spread sheet every 250 seconds with stopping time of 5 seconds. During the first set of experiments, X and Y feed drive units are operated in to-and fro motion with a feed rate of 4m/min for the first 35 minutes, next 13 minutes with 4.8m/min feed rate for idle running, i.e without cutting. Finally the drive unit is put off and allowed to cool naturally for 2 hours.

In the second set of experiments, both X and Y axes feed drive units are operated simultaneously with a feed rate of 4 m/min for the first 40 minutes, 4.8 m/min for the next 45 minutes and finally cooled down for the next 70 minutes. The stroke is 200 mm in both cases. The procedure is continued till the completion of operation time. The measured temperature data is used to optimize the number of temperature sensors which is explained in the next section.

The temperature trends for the combined loading cycle measured on X-axis and Y-axis thermal key points are shown in Fig.4 and Fig.5 respectively. The temperature patterns exhibited the same trend. This reveals that, despite the varying free traversing speeds of the table, the temperature behaviour remains

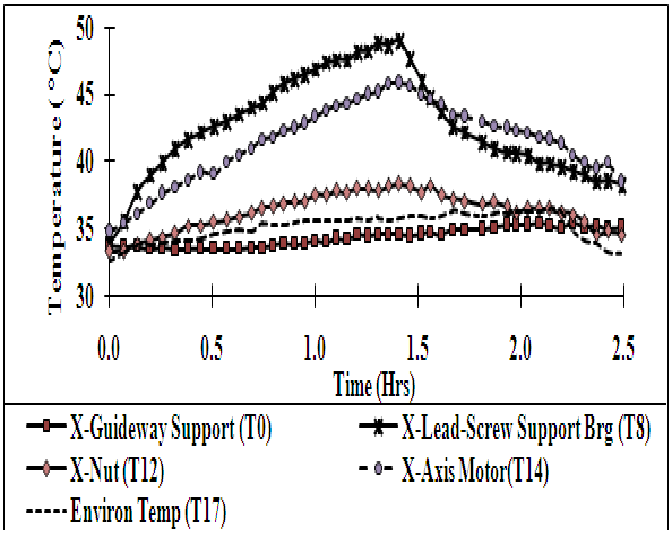

Fig.4 Measured temperatures on X-Guideway for combined table movement

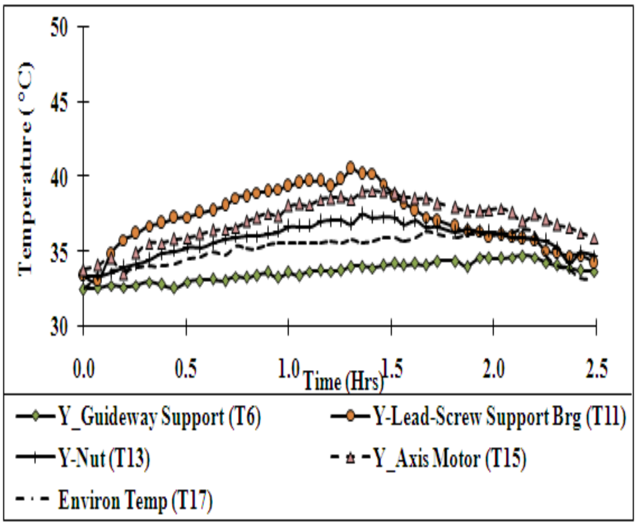

Fig.5Measured temperatures on Y-Guideway for combined table movement

similar, never the less there is a variation in magnitude. The deformation pattern during combined axis free traversing is almost linear and drops gradually once the table traversing along X-axis is stopped. This is shown in Fig.6.

However, a peculiar phenomenon in X-axis deformation has been observed in combined axis free traversing of table, during the first one hour of table traversing. A sudden rise in the deformation at TCP measured along X-axis was noticed. The reason for this phenomenon can be attributed to the unstable thermal behaviour that arises due to non-symmetric machine tool structure in Y-axis. The temperature behaviour of the key points of lower table (Y-axis table) is not identical neither in individual free traversing along Y-axis nor in the combined axis traversing. The magnitudes of both temperature and deformations with respect to TCP along Y- axis are less during combined axis free traversing. This phenomenon indicates that there is temperature gradient from lower table to the upper table. Similar observations were also noticed by other researchers in their investigations on CNC machines of feed drive system.

Thermal Sensitivity Analysis

The thermal key points to which the temperature sensors are attached are the best points to accurately model the thermal errors by correlating their temperatures to the thermal errors.

However, recognising all the thermal key points on the machine tool is not an easy task. A few studies have made use of optimization algorithms such as

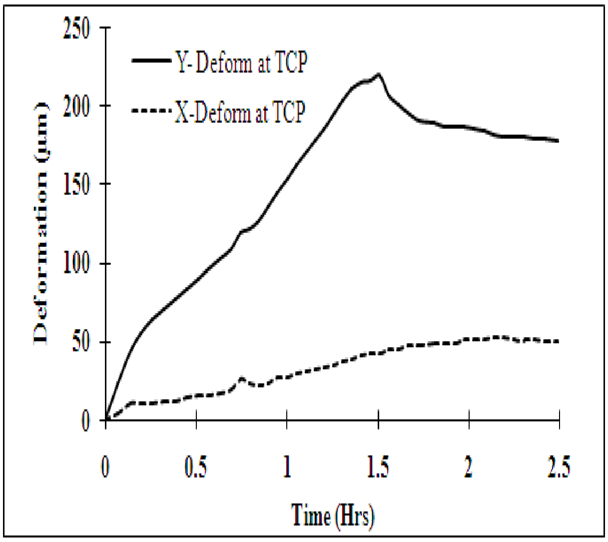

FIG.6 MEASURED DEFORMATIONS AT TCP ALONG X AND Y-COMPONENT FOR COMBINED TABLE

genetic algorithm to solve this problem. When the numbers of thermal points chosen by engineering thumb rule are less, it is uneconomical to use genetic algorithm. Hence, in this study a more simple method called sensitivity analysis has been used for optimization of thermal key points.

Sensitivity is the property of a system, or part of a system, that indicates how the system reacts to stimuli. The ratio of change in thermal error to the change in temperature in the system is called thermal error sensitivity. It can be expressed as,

$$S = \lim_{\Delta T \to O} \left[\frac{\delta'}{\Delta T} \right] \quad (1)$$

When the sample interval is small, the thermal error sensitivity can be approximated by $\left[\frac{\delta'}{\Delta T} \right]$. An accurate thermal error model should include the contribution of as many candidate points as possible and can be realized in the following ways: 1) Increasing the number of thermal key points directly; 2) enlarging the difference of the thermal error sensitivity among the thermal key points. The first option may not be feasible from the economic and practical point of view. The second option of enlarging the difference of thermal error sensitivity among thermal key points has been employed in the present study.

In the sensitivity analysis, the thermal error sensitivity of one thermal key point is compared with all other key points. So, all possible combinations of difference in thermal error sensitivity $D_{i,k}$ between the key points are computed. The method of evaluating sensitive points is consolidated in Table I. Where, δ is deformation measured at TCP in (µm) along the X-Axis component, $\delta' = \delta_i \sim \delta i_{+1} =$ is the difference between successive deformations measured at TCP in (µm) along the X-Axis component, Ti is temperature measured at different sensor locations corresponding to time increment in Degree Celsius,

$\Delta T_i = T_i \sim T_{i+1}$ = is the difference between successive temperature measurements at different sensor locations corresponding to time increment in Degree Celsius, $S_i = S_i \sim S_{i+1}$ = is the difference between successive sensitivity points corresponding to time increment in (µm/°C),

$D_{i,k} = S_i \sim S_k$ = Difference between different sensitivity values. Table II gives the possible combinations of the sensitive point differences.

TABLE 1 SENSITIVITY VALUES FOR X-AXIS DEFORMATION FOR COMBINED LOADING

Time (Hour)	δ (µm)	δ′ (µm)	T_0 °C	ΔT_0 °C	S_0 (µm/°C)	---	$D_{1,17}$ (µm/°C)
0	0	0	33.76	0	0	--	0
0.07	0.4	0.4	33.58	0.18	1.51	--	6.459
0.14	28.2	27.8	33.65	0.07	162.91	--	9.606
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1.12	94.2	8.1	34.48	0.08	95.01	--	6.77
1.39	91.7	2.5	34.51	0	5.88	--	2.67

TABLE 2 POSSIBLE COMBINATIONS OF THERMAL KEY POINTS DIFFERENCES

KEY POINTS	D1	D2	D3	----	D17
D1	----	D1,2	D1,3	-----	D1,17
D2	----	----	D2,3	-----	D2,17
D3	----	-----	----	----	D3,17
---	----	----	----	----	----
D17	---	----	----	----	----

The summations of these individual differences are plotted in a graph against different time intervals. Fig.7 shows the difference in thermal error sensitivity curve for X-axis feed drive and Y-Axis feed drive systems. The largest minima for X-axis sensitivity is 843.406 (µm/ºC). The maxima points which are above 843.406 are the combination of the thermal key points of the X-axis and Y-axis feed drive system (as shown in Fig 7) are (1, 8),(1, 10), (1, 12), and (1,15). The corresponding key points refer to their respective location as in Fig.1.

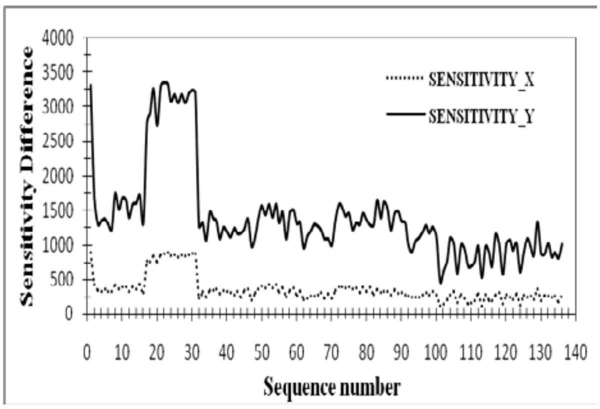


FIG.7. DIFFERENCE IN THERMAL SENSITIVITY OF KEY POINTS FOR X- AXIS & Y-AXIS

The thermal key points which appear at least once in the above list are the most predominant source factor that determines thermal error. Hence, the selected key points are 1, 8, 10, 12and 15. They are found to be more sensitive in the analysis. The eliminated key points also show temperature changes but their contribution in determining the thermal error is not significant.

The above procedure is repeated for determining the thermal sensitive points in Y-axis feed drive system for the corresponding loading. Accordingly, the largest minima here is 3078.94 (µ/ºC). The maxima points which are above 3078.94 are (1,4), (1,7), (1,10), (1,12) and (1,15).Thus the selected key points are 1,4 and 7,10,12 and 15.

For individual axis loading, separate sensitivity analysis is not carried out. The temperature data measured at thermal key points during combined axis loading are used to predict the thermal deformation for individual loading cycle. The next section describes the development of thermal error model based on above optimized temperature key points.

Thermal Error Modeling

The change of temperature in different parts of the machine tool leads to thermal deformation which ultimately leads to a decrease in the machining accuracy of parts being produced. To map the deformation of all these parts is difficult in developing accurate deformation model. Therefore using statistical analysis to correlate the deformation of single part (TCP in this case) with respect to different temperature source is considered here.

Multivariable Regression Analysis

The two-variable regression analysis is often inadequate in practice. Extending the two variable regression analysis to cover models involving more than two variables leads to multivariable regression models, i.e. the model in which the dependent variable,

or regressand, Y depends on two or more explanatory variables or regressors. The model that represents the behaviour of the variation of thermal errors is written in the form,

$$Y_i=\beta_1+\beta_2X_i+\beta_3X_{i2}+\beta_{11}X_{i2}+\beta_{22}X_{i22}....+\beta_kX_{ki2}+u, \qquad (2)$$

i=1,2,...,n

The co-efficients β_1, β_2,........ β_k are partial regression co-efficients, u is regression variable (error).

The deformations of X-component and Y-components have been predicted using the input temperature data from optimized temperature key points for combined load cycle. The non-linear model is as given below with the R^2 value mentioned after the corresponding equations. Excel-stat software has been used to model the thermal deformation in both X and Y-axes (δX and δY) of horizontal feed drives as given below.

$$\begin{aligned}\delta_X &= -1.29(E+4)+5.69(E+1)\left(T_1^1\right)+2.38(E+1)\left(T_4^1\right)\\ &-6.47\left(T_7^1\right)+22.36\left(T_8^2\right)-6.6(E+1)\left(T_{10}^1\right)-21.48\left(T_{12}^1\right)\\ &+9.15\left(T_{15}^1\right)-8.14\left(T_1^2\right)-3.47\left(T_4^2\right)+0.08\left(T_7^2\right)-0.301\left(T_8^2\right)\\ &+0.96\left(T_{10}^2\right)+0.29\left(T_{12}^2\right)-9.46(E-2)\left(T_{15}^2\right) \qquad (3)\\ &\text{with} \quad R^2=0.973\end{aligned}$$

$$\begin{aligned}\delta_Y &= -6.7(E+4)+3.02\left(T_1^1\right)+9.08(E+2)\left(T_4^1\right)\\ &-2.52(E+2)\left(T_7^1\right)+1.3\left(T_8^1\right)+2.5(E+1)\left(T_{10}^1\right)-6.8(E+1)\left(T_{12}^1\right)\\ &+2.52(E+2)\left(T_{15}^1\right)-4.3(E+1)\left(T_1^2\right)-1.3(E+1)\left(T_4^2\right)+3.5\left(T_7^2\right)\\ &-0.18\left(T_8^2\right)+5.6(E-2)\left(T_{10}^2\right)+0.86\left(T_{12}^2\right)-3.3\left(T_{15}^2\right) \qquad (4)\\ &\text{with} \quad R^2=0.975\end{aligned}$$

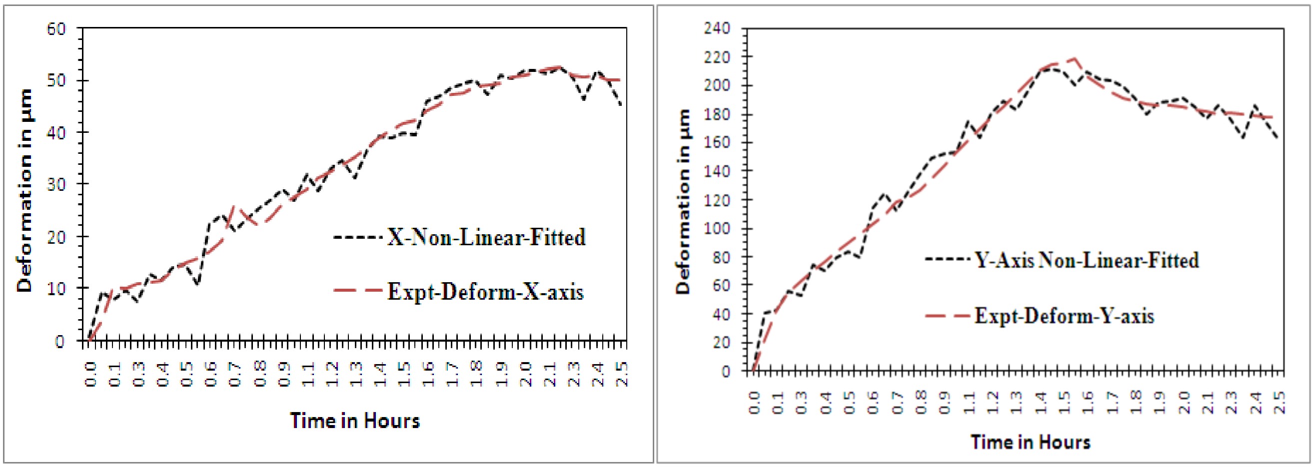
The comparison of non-linear statistical regression model and experimental values are as shown in the Fig.8a & b.

Conclusions

Using sensitivity analysis, the thermal key points are reduced from seventeen to seven (T1,T4,T7,T8,T10,T12,T15). Using the temperature data from these thermal key points, the non-linear regression models are developed for the combined loading for X and Y-axis feed drives. The comparison of non-linear regression prediction using optimized key points and experimental values shows good correlation, also the statistical analysis of adjusted R^2 value for X-axis and Y-axis prediction is 0.973 and 0.975 respectively.

The R^2 value nearly reaches 1 (0.998) for both axes models if all thermal key points are taken for developing the model. But, this certainly raises the issues like multi-colinearity in the model and it is also not economical to consider all the key points. It is depicted from the Fig.8 that, the correlation between temperature-deformation model is almost linear hence non-linear model is not required. One more hazard of using non-linear model is, it proves to be best fit for the data in hand, but may turn in unexpected direction when extrapolated beyond the range of data.

The method used in this paper to optimize the thermal key point as well as to develop the mathematical model is simple to calibrate. Also the implementation of the mathematical model is cost effective for thermal error compensation compared to other methods like ANN, Baysen approach etc. The developed model can be interfaced to machine controller through microprocessors in order to monitor and control the thermal deformations. The method can be extended to



(a) (b)

FIG.8 COMPARISON OF NON-LINEAR REGRESSION AND EXPERIMENTAL DEFORMATIONS AT TCP, A) MEASURED ALONG X-AXIS, B) MEASURED ALONG Y-AXIS

develop the model and interfaced with controller for Z-axis feed drive also.

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